

Extending Eventually Consistent Cloud Databases for Enforcing Numeric Invariants

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Abstract—Geo-replicated databases often operate under the principle of eventual consistency to offer high-availability with low latency on a simple key/value store abstraction. Recently, some have adopted commutative data types to provide seamless reconciliation for special purpose data types, such as counters. Despite this, the inability to enforce numeric invariants across all replicas still remains a key shortcoming of relying on the limited guarantees of eventual consistency storage.

We present a new replicated data type, called bounded counter, which adds support for numeric invariants to eventually consistent geo-replicated databases. We describe how this can be implemented on top of existing cloud stores without modifying them, using Riak as an example. Our approach adapts ideas from escrow transactions to devise a solution that is decentralized, fault-tolerant and fast. Our evaluation shows much lower latency and better scalability than the traditional approach of using strong consistency to enforce numeric invariants, thus alleviating the tension between consistency and availability.

I. INTRODUCTION

Scalable cloud databases with a key/value store interface have emerged as the platform of choice for providing online services that operate on a global scale, such as Facebook [15], Amazon [11], or Yahoo! [9]. In this context, a common technique for improving the user experience is geo-replication [11], [9], [27], i.e., maintaining copies of application data and logic in multiple data centers scattered across the globe. This decreases the latency for handling user requests by routing them to nearby data centers, but at the expense of resorting to weaker data consistency guarantees, in order to avoid a costly coordination across replicas for executing operations.

When executing under such weaker consistency models, applications have to deal with concurrent operations executing without being aware of each other, which implies that a merge strategy is required for reconciling concurrent updates. A common approach is to rely on a *last writer wins* strategy [19], [20], [15], but this is not appropriate in all situations. A prominent example is the proper handling of counters, which are a useful abstraction for implementing features such as *like* buttons, votes and ad and page views, and all sorts of resource counting. For counters, using *last writer wins* leads to lost updates, breaking the intended semantics. To address this limitation, cloud databases, such as Cassandra [1], DynamoDB and Riak[6], have extended their interfaces with support for correct counters, implemented using specific merge algorithms.

Even though these approaches provide a principled handling of concurrent updates to counter objects, they fall short on supporting the enforcement of crucial invariants or database integrity constraints, which are often required for maintaining

correct operation [17]. Real world examples where enforcing invariants is essential are advertisement services, virtual wallets or to maintain stocks. However, enforcing this condition using counters implemented on eventually consistent cloud database is impossible. This is because counter updates can occur concurrently, making it impossible to detect if the limit is exceeded before the operation concludes.

Maintaining this type of invariants would be trivial in systems that offer strong consistency guarantees, namely those that serialize all updates, and therefore preclude that two operations execute without seeing the effects of one another [10], [27], [17]. The problem with these systems is that they require coordination among replicas, leading to an increased latency. In particular, in a geo-replicated scenario, this latency may amount to hundreds of milliseconds, which suffices to impact application usability [23].

In this paper we show that it is possible to achieve the best of both worlds, i.e., that fast geo-replicated operations on counters can coexist with strong invariants. To this end, we propose a novel abstract data type called a *Bounded Counter*. This replicated object, like conventional CRDTs [24], allows for operations to execute locally, automatically merges concurrent updates, and, in contrast to previous CRDTs, also enforces numeric invariants while avoiding coordination in most cases. Implementing *Bounded Counter* in a fast and portable way required overcoming a series of challenges, which form the main technical contributions of this work.

First, we propose an extension to the main idea behind escrow transactions [21], which is to partition the difference between the current value of a counter and the limit to be enforced among existing replicas. These parts are distributed among replicas, who can locally execute operations that do not exceed their allocated part. Unlike previous solutions that include some central authority and are often based on synchronous interactions between nodes [21], [5], [22], [25], our approach is completely decentralized and asynchronous, with each replica relying only on a local and possibly stale view of the information and on peer-to-peer asynchronous interactions. This design makes it easy to deploy our system, since we do not need to add a new master server (or replica group) that controls the allocation of operations on the counter. Furthermore, this avoids situations where the temporary unreachability of the data center where the master server is located can prevent operations from making progress.

Second, and building on the fact that we did not have to add any new master servers to enforce invariants, we show how it is possible to layer our design on top of existing

eventually consistent storage systems, while making very few assumptions about the underlying system. In particular, we only assume that the underlying storage system executes operations in a serializable way in each replica (not necessarily by the same order across replicas) and that it provides a reconciliation mechanism for merging concurrent updates. This makes our solution generic and portable, but raises the bar for achieving a performance that is comparable to directly accessing the underlying storage. Furthermore, we propose two alternative designs, where the first one is implemented using only a client-side library, whereas the second one includes a server side component deployed in a distributed hash table, which provides better scalability by minimizing the number of operations executed in the underlying storage system.

The evaluation of our prototypes running on top of Riak shows that: 1) when compared to using weak consistency, our approach with the cache and a write batching mechanism has higher throughput with a very small increase in latency, while guaranteeing that invariants are not broken; 2) when compared to using strong consistency, our approach can enforce invariants without paying the latency price for replica coordination, which is considerable for all but the local clients; 3) the client based design performs well under low contention, but does not scale when contention on the same counter is large; 4) the server based design scales well with the number of clients executing operations, providing even higher throughput than weak consistency.

The remainder of the paper is organized as follows. Section II overviews our solution and its requirements; Section III introduces the *Bounded Counter* CRDT; Section IV presents our two designs that extend Riak with numeric invariant preservation; Section V evaluates our prototypes; Section VI discusses extensions to the proposed design; Section VII discusses related work; and Section VIII concludes the paper.

II. SYSTEM OVERVIEW

A. Assumptions

We target a typical geo-replicated scenario, with copies of application data and logic maintained in multiple data centers (DC) scattered across the globe. End clients contact the closest DC for executing application operations in the application server running in that DC. The execution of this application logic leads to issuing a sequence of operations on the database system where application data resides.

We consider that system processes (or nodes) are connected by an asynchronous network (i.e., subject to arbitrary delays, including partitions). We assume a finite set $\Pi = p_0, p_1, \dots, p_{n-1}$ of processes who may fail by crashing. A crashed process may remain crashed forever, or may recover with its persistent memory intact. A non-crashed process is said to be *correct*.

For simplicity, our presentation considers a single data object replicated in all processes of Π , with r_i representing the replica of the object at process p_i . The model trivially generalizes to the case where multiple data objects exist – in such a case, for each object o , we need to consider only the set Π^o of the processes that replicate o .

```
% Regular data operations
get(key): object | fail
put(key, object): ok | fail

% Bounded Counters operations
create(key, type, bound): ok | error
read(key): integer | error
inc(key, delta, flag): ok | fail | retry
dec(key, delta, flag): ok | fail | retry
```

Fig. 1. System API.

B. System API

Our middleware system is built on top of a weakly-consistent key-value database. Figure 1 summarizes the programming interface of our system, with the usual *get* and *put* operations for accessing regular data, and additional operations for creating a new *Bounded Counter*, reading its current state, and incrementing or decrementing its value. As any other data, InvCounters are identified in all operations by an opaque key.

The *create* operation creates a new bounded counter. The *type* argument specifies if it is an *upper*- or a *lower*- *Bounded Counter*, and the *bound* argument provides the global invariant limit to be maintained – e.g., *create*("X", *upper*, 1000) creates a *Bounded Counter* that maintains the invariant that the value must be *smaller or equal to 1000*. The counter is initialized to the value of the bound.

The *read* operation returns the current value of the given counter. The returned value is computed based on local information and it may not be globally accurate. To update a counter, the application submits *inc* or *dec* operations. These operations include a *flag* to decide on whether the execution is strictly local or whether global execution is attempted. In both cases, the operation attempts to run locally first. When the local information cannot guarantee that the value remains within bounds, in the case of a strictly local operation, the API returns an error and a hint regarding whether global execution is likely to succeed; otherwise, in the case of a global operation, the system tries to contact remote replicas to safely execute to operation and only returns an error if this coordination with remote replicas cannot ensure the preservation of the invariant (namely when the counter has reached its limit).

C. Consistency Guarantees

We build our middleware on top of an eventually consistent database, extending the underlying guarantees with invariant preservation for counters. In particular, the eventual consistency model means that the outcome of each operation reflects the effects of only a subset of the operations that all clients have previously invoked – these are the operations that have already been executed by the replica that the client has contacted. However, for each operation that successfully returns at a client, there is a point in time after which its effect becomes visible to every operation that is invoked after that time, i.e., operations are eventually executed by all replicas.

In terms of the invariant preservation guarantee, this means that the bounds on the counter value are never violated, neither *locally* nor *globally*. By *locally*, this means that the bounds must be obeyed in each replica at all times, i.e., the subset of operations seen by the replica must obey:

$$\text{lower bound} \leq \text{initial value} + \sum \text{inc} - \sum \text{dec} \leq \text{upper bound}.$$

By *globally*, this means that, at any instant in the execution of

the system, when considering the union of all the operations executed by each replica, the same bounds must hold.

Note that the notion of causality is orthogonal to our design and guarantees, in the sense that if the underlying storage system offers causal consistency, then we also provide numeric invariant-preserving causal consistency.

D. Enforcing Numeric Invariants

To enforce numeric invariants, our design borrows ideas from the escrow transactional model [21]. The key idea of this model is to consider that the difference between the value of a counter and its bound can be seen as a set of rights to execute operations. For example, in a counter, n , with initial value $n = 40$ and invariant $n \geq 10$, there are 30 ($40 - 10$) rights to execute decrement operations. Executing $dec(5)$ consumes 5 of these rights. Executing $inc(5)$ creates 5 rights. In this model, these rights are split among the replicas of the counter – e.g. if there are 3 replicas, each replica can be assigned 10 rights. If the rights needed to execute some operation exist in the local replica, the operation can safely execute locally, knowing that the global invariant will not be broken – in the previous example, if the decrements of each replica are less or equal to 10, it follows that the total number of decrements does not exceed 30, and therefore the invariant is preserved. If not enough rights exist, then either the operation fails or additional rights must be obtained from other replicas.

Our approach encompasses two components that work together to achieve the goal of our system: a novel data structure, the *Bounded Counter* CRDT, to maintain the necessary information for locally verifying whether it is safe to execute an operation or not; and a middleware layer to manipulate instances of this data structure stored in the underlying cloud database. The first component is detailed in Section III, while alternative designs to the second part are detailed in Section IV.

III. DESIGN OF BOUNDED COUNTER CRDT

This section presents the design of *Bounded Counter*, a CRDT that can be used to enforce numeric invariants without requiring coordination for most operation executions. Instead, coordination is normally executed outside of the normal execution flow of an operation and amortized over multiple operations.

A. CRDT Basics

Conflict-free replicated data types (CRDTs) [24] are a class of distributed data types that allow replicas to be modified without coordination, while guaranteeing that replicas converge to the same correct value after all updates are propagated and executed in all replicas.

Two types of CRDTs have been defined: *operation-based CRDTs*, where modifications are propagated as operations (or patches) and executed on every replica; and *state-based CRDTs*, where modifications are propagated as states, and merged with the state of every replica.

In this work, we have adopted the state-based model, as we have built our work on top of a key-value store that synchronizes replicas by propagating the state of the database objects. In this model, one operation submitted in one site executes in the local replica. Updates are propagated among replicas

```

payload integer[n][n] R, integer[n] U, integer min
    initial [[0,0,...,0], ..., [0,0,...,0]], [0,0,...,0], K
query value () : integer v
    v = min +  $\sum_{i \in Ids} R[i][i] - \sum_{i \in Ids} U[i]$ 
query localRights () : integer v
    id = repId() %Id of the local replica
    v = R[id][id] +  $\sum_{i \neq id} R[i][id] - \sum_{i \neq id} R[id][i] - U[id]$ 
update increment (integer n)
    id = repId()
    R[id][id] = R[id][id] + n
update decrement (integer n)
    pre-condition localRights()  $\geq n$ 
    id = repId()
    U[id] = U[id] + n
update transfer (integer n, replicaId to): boolean b
    pre-condition b = (localRights()  $\geq n$ )
    from = repId()
    R[from][to] := R[from][to] + n
update merge (S)
    R[i][j] = max(R[i][j], S.R[i][j]),  $\forall i, j \in Ids$ 
    U[i] = max(U[i], S.U[i]),  $\forall i \in Ids$ 

```

Fig. 2. *Bounded Counter* for maintaining the invariant *larger or equal to K*.

in peer-to-peer interactions, where a replica r_1 propagates its state to another replica r_2 , which merges its local and received state, by executing the *merge* function.

State-based CRDTs build on the definition of a join semi-lattice (or just semi-lattice), which is a partial order \leq equipped with a *least upper bound* (LUB) \sqcup for all pairs: $m = x \sqcup y$ is a Least Upper Bound of $\{x, y\}$ under \leq iff $x \leq m \wedge y \leq m \wedge \forall m', x \leq m' \wedge y \leq m' \Rightarrow m \leq m'$.

It has been proven that a sufficient condition for guaranteeing the convergence of the replicas of state-based CRDTs is that the object conforms the properties of a monotonic semi-lattice object [24], in which: (i) The set S of possible states forms a semi-lattice ordered by \leq ; (ii) The result of merging state s with remote state s' is the result of computing the LUB of the two states in the semi-lattice of states, i.e., $merge(s, s') = s \sqcup s'$; (iii) The state is monotonically non-decreasing across updates, i.e., for any update u , $s \leq u(s)$.

B. Bounded Counter CRDT

We now detail the *Bounded Counter*, a CRDT for maintaining the invariant *larger or equal to K*. The pseudocode for *Bounded Counter* is presented in Figure 2.

Bounded Counter state: The *Bounded Counter* must maintain the necessary information to verify whether it is safe to locally execute operations or not. This information consists in the rights each replica holds (as in the escrow transactional model [21]).

To maintain this information, for a system with n replicas, we use two data structures. The first, R is a matrix of n lines by n columns with: $R[i][i]$ recording the *increments* executed at r_i , which define an equal number of rights initially assigned to r_i ; $R[i][j]$ recording the rights transferred from r_i to r_j . The second, U is a vector of n lines with $U[i]$ recording the successful *decrements* executed at r_i , which consume an equal number of rights.

R	r_0	r_1	r_2	U
r_0	30	10	10	5
r_1	0	1	0	4
r_2	0	0	0	2

Fig. 3. Example of the state of *Bounded Counter* for maintaining the invariant *larger or equal to 10*.

For simplicity, our specification assumes every replica maintains a complete copy of these data structures, but we later discuss how to avoid this in practice.

Operations: When a counter is created, we assume that the initial value of the counter is equal to the minimum value allowed by the invariant, K . Thus, no rights are assigned to any replica and both R and U are initialized with all entries being equal to 0. To overcome the limiting assumption of the initial value being K , we can immediately execute an *increment* operation in the freshly created *Bounded Counter*. Figure 3 shows an example of the state of a *Bounded Counter* for maintaining the invariant *larger or equal to 10*, with initial value 40. This initial value led to the creation of 30 rights assigned to r_0 – this value is recorded in $R[0][0]$.

An *increment* executed at r_i updates the number of increments for r_i by updating the value of $R[i][i]$. In the example of Figure 3, the value of $R[1][1]$ is 1, which is the result of incrementing the counter by 1 in r_1 .

A *decrement* executed at r_i updates the number of decrements for r_i by updating the value of $U[i]$. This operation can only execute if r_i holds enough rights before executing the operation. The *decrement* operation fails if not enough local rights exist. In the example of Figure 3, the values of U reflect the execution of 5, 4 and 2 decrements in r_0 , r_1 and r_2 , respectively.

The rights the local replica r_i holds, returned by function *localRights*, are computed by: (a) adding the increments executed in the local replica, $R[i][i]$; (b) adding the rights transferred from other replicas to r_i , $R[j][i], \forall j \neq i$; (c) subtracting the rights transferred from r_i to other replicas, $R[i][j], \forall j \neq i$; and (d) subtracting the decrements executed in r_i , $U[i]$. In the example of Figure 3, replica r_0 holds 5 rights (obtained from $30 + (0+0) - (10+10) - 5$), allowing to locally decrement the counter by up to 5.

The operation to retrieve the current value of the counter consists of: (a) adding the minimum value, K ; (b) adding the sum of increment operations executed at any replica, $R[i][i], \forall i$; and (c) subtracting the sum of the decrement operations executed at any replica, $U[i], \forall i$. In the example of Figure 3, the current value is 30 (obtained from $10 + (30+1) - (5+4+2)$).

The operation *transfer* executed at replica r_i transfers rights from r_i to some other replica r_j , by updating the value recorded in $R[i][j]$. This operation can only execute if enough local right exist. In the example of Figure 3, transfers of 10 rights from r_0 to each of r_1 and r_2 are recorded in the values of $R[0][1]$ and $R[0][2]$.

The *merge* operation is executed during peer-to-peer synchronization, when a replica receives the state of a remote replica. The local state is updated by just taking, for each entry of both data structures, the maximum of the local and the received value.

Correctness: For showing the correctness of *Bounded Counter*, it is necessary to show that all replicas of *Bounded Counter* eventually converge to the same state, i.e., that *Bounded Counter* is a correct CRDT, and that the execution of concurrent operations will not break the invariant. We now sketch an argument for why these properties are satisfied.

For showing that replicas eventually converge to the same state, it is necessary to prove that the specification is a monotonic semi-lattice object. As the elements of R and U are monotonically increasing (since operations never decrement the value of these variables), the semi-lattice properties are immediately satisfied – two states, s_0, s_1 , are related by a partial order relation, $s_0 \leq s_1$, whenever all values of R and U in s_1 are greater or equal to the corresponding values in s_0 (i.e., $\forall i, j, s_0.R[i][j] \leq s_1.R[i][j] \wedge s_0.U[i] \leq s_1.U[i]$). Furthermore, the merge of two state is the LUB, as the function just takes the maximum

To guarantee that the invariant is not broken, it is necessary to guarantee that a replica does not execute an operation (*decrement* or *transfer*) without holding enough rights to do it. As operations execute sequentially and verify if the local replica holds enough rights before execution, it is necessary to prove that if a replica believe it has N rights, it owns at least N rights. The construction of the algorithms guarantees that line i of R and U is only updated by operations executed at replica r_i . Thus, replica r_i necessarily has the most recent value for line i of both R and U . As rights of replica r_i are consumed by *decrement* operations, recorded in $U[i]$, and transfer operations, recorded in $R[i][j]$, it follows immediately that replica r_i knows of all rights it has consumed. Thus, when computing the local rights, the value computed locally is always conservative (as replica r_i may not know yet of some transfer to r_i executed by some other replica). This guarantees that the invariant is not broken when operations execute locally in a single replica.

We wrote the specification of *Bounded Counter* in TLA [16] and successfully verified that the invariant holds for all the cases that the tool generated.

Extensions: It is possible to define a *Bounded Counter* that enforces an invariant of the form *smaller or equal to K* by using a similar approach, where rights represent the possibility of executing *increment* operations instead of *decrement* operations. The specification would be similar to the one presented in Figure 2, with the necessary adaptations to the different meaning of the rights.

A *Bounded Counter* that can maintain an invariant of the form *larger or equal to K_0 and smaller or equal to K_1* can be created by combining the information of two *Bounded Counter*s, one for each invariant, and updating both on each operation.

Optimizations: The state of *Bounded Counter*, as presented, has complexity $O(n^2)$. In practice, the impact of this is expected to be small as the number of data centers in common deployments is typically small and each data center will typically hold a single logical replica.

In the cases when this is not true, we can leverage the following observations to lower the space complexity of *Bounded Counter*s up to $O(n)$. For computing the local rights, replica r_i only uses the line i and column i of R and line i of U . For computing the local value of the counter, replica i additionally

uses entries $R[i][i], \forall i$ and the remaining entries of U . This leads to a space complexity of $4.n$ for storage, which compares with $2.n$ as the minimal complexity of a state-based counter [8].

In this case, when synchronizing, a replica only needs to send the information both replicas store. Thus, a replica r_i would send to r_j only $R[i][i], \forall i, R[i][j]$ and U^1 , lowering the space complexity for messages to $2.n$.

When this optimization is not in place, and every replica maintains the complete data structure, we can still lower the communication costs by propagating the information epidemically. This means that it is not necessary for every replica to communicate directly with every other replica. In particular, we can allow for the communication to be reactive instead of proactive: a replica r_i only needs to communicate directly with r_j when it transfers rights to r_j (e.g., upon request in order to execute an operation) so that r_j knows about the new rights. Note that the lack of communication does not affect the correctness regarding the invariant violation, as each replica always has a conservative view on its available rights.

IV. MIDDLEWARE FOR ENFOCING NUMERIC INVARIANTS

We now present two middleware designs for extending Riak database with numeric invariants, using the *Bounded Counter*. The proposed designs can be applied to any database that provides the following two properties, essential for *Bounded Counter* to work properly. First, each replica needs to execute operations referring to each counter in a serializable way, i.e., as if they had been executed in sequence. This does not, however, preclude concurrency: operations for different counters are not constrained by this requirement, and even within the same counter there are protocols that allow for some concurrency while maintaining the illusion of a serializable execution. This serialization is necessary to guarantee that two concurrent operations do not use the same rights. Second, the replication model must ensure no lost updates, i.e., updates executed concurrently in different replicas must be merged using the CRDT merge function. This is necessary for the CRDT to work properly.

Before presenting the middleware designs, we present an overview of the functionalities of Riak that are relevant for the deployment of *Bounded Counters*.

A. Overview of Riak 2.0

Riak 2.0 is a key/value database inspired in Dynamo [11]. It support geo-replication in its Enterprise Edition, where each DC maintains a full replica of the database. Riak provides an API supporting a read (*get*) and write (*put*) interface, where a write associates a new value with a key, and a read returns the value(s) associated with the key.

By default, writes on a key can proceed concurrently, with the system maintaining the multiple concurrent versions and exposing them to clients in subsequent read operations. Additionally, Riak includes native support for storing CRDTs, dubbed Riak data types, where concurrent writes are automatically merged.

Riak keys can be marked as strongly consistent. For these keys, Riak uses a conditional writing mode where a write fails

¹Replicas r_i and r_j also share $R[j][i]$, but as this value is only updated at r_j , it is not necessary to send it.

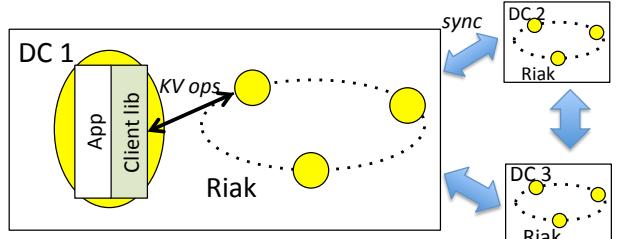


Fig. 4. Client-based middleware for deploying *Bounded Counters*.

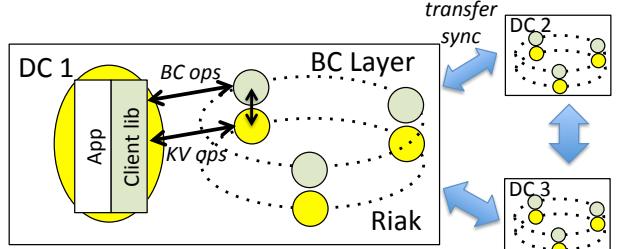


Fig. 5. Server-based middleware for deploying *Bounded Counters*.

if a concurrent write has been executed. These key are not geo-replicated (each DC has its local view of the data) and they cannot store a Riak data type object.

B. Alternative 1: Client-based Middleware

Our first design, depicted in Figure 4, is based on a client-side middleware. Supporting operations on *Bounded Counters* is fairly simple, given the functionality provided by Riak.

The state of a *Bounded Counter* is stored as an opaque object in the Riak database, which is marked as strongly consistent. Rights for executing operations in a *Bounded Counter* are associated with each DC, i.e., each DC is considered as a single replica for a *Bounded Counter*. An increment (resp. decrement) executes in the client library by first reading the current value of the counter (executing a *get* operation in Riak), then executing the increment (resp. decrement) operation in the *Bounded Counter* and writing the new value of the counter back into the database. If the operation in the *Bounded Counter* fails, the client can try to obtain additional rights by requesting the execution of a *transfer* operation from another DC. If the operation in the CRDT succeeds but the conditional write fails, the operation must be re-executed until it succeeds.

Given that *Bounded Counters* are marked as strongly consistent, updates are serialized in each DC through the conditional writing mechanism. Concurrent updates to the same *Bounded Counter* can only appear due to geo-replication. If this is the case, then concurrent versions can be merged by the client library when reading the counter.

For propagating the updated values across DC, we were not able to reuse the geo-replication mechanism from Riak, since it does not support multi-data center replication for objects that use strong consistency. As such, we had to implement a custom synchronization mechanism for *Bounded Counters*. This custom synchronization forwards modified counters to other DCs periodically. A DC receiving a remote version of a counter, merges the received version with the local version.

C. Alternative 2: Server-based Middleware

The client-based middleware has an important limitation, as pointed out by the evaluation in Section V: the conditional

writing mechanism for serializing operation execution works well under low load, but leads to an increased number of failed writes when the load increases. To address this issue, we propose a server-based middleware design that serializes all operations executed in each DC for each counter.

The server-based middleware is built using a DHT communication substrate (riak_core [13] in our prototype) running side by side with each node of the Riak database. The key feature that is employed is the ability to *lookup* the DHT node that is responsible for a given key. This primitive is used to route all requests for a given key to the same node, which serializes their execution. For operations on regular objects, the client library calls Riak directly (without contacting DHT nodes).

When an application wants to execute an operation in a counter, the operation is sent to the DHT node responsible for that counter. The DHT node executes the operation by reading the counter from Riak, executing the operation and writing back the new value. *Bounded Counters* are marked as strongly consistent, with writes being executed using conditional write. In the normal case, when there are no reconfigurations, the conditional write will succeed, since a single DHT node is responsible for any given key and executes all operations for each counter in sequence.

In contrast, when a new nodes enters the DHT or some node fails, the DHT is automatically reconfigured and it becomes possible that two nodes concurrently process two operations for the same key. In this case, only the first write will succeed, since the following concurrent writes will fail due to the conditional write mechanism. This guarantees the correctness of the system, by serializing all updates.

Since Riak does not geo-replicate keys marked as strongly consistent, our middleware had to include a mechanism for propagating updates to *Bounded Counters* to other DCs. To this end, each DHT node periodically propagates its updated entries to the corresponding DHT nodes in other DCs. With this approach, each value that is sent can include the effects of a sequence of operations, thus reducing the communication overhead. As in the previous version, when a *Bounded Counter* is received in a DC from another DC, it is merged with the local replica using the CRDT merge function. For other objects, we rely on normal built-in Riak multi-data center replication.

Optimizations: Our prototype includes a number of optimization to improve its efficiency. The first optimization is to cache *Bounded Counters* at the middleware layer. This allows us to reduce the number of Riak operations necessary for processing each update on a *Bounded Counter* from two to one – only the write is necessary.

Under high contention in a *Bounded Counter*, the design described so far is not very efficient, since an operation must complete before the next operation starts being processed. In particular, since processing an update requires writing the modified *Bounded Counter* back to the Riak database, which involves contacting remote nodes, each operation can take a few milliseconds to complete. To improve throughput, while a remote write to Riak is taking place, the operations that are received are executed in the local copy of the *Bounded Counter*. If the counter cannot be incremented or decremented, the result is immediately returned to the client. Otherwise, no

result is immediately returned and the operation becomes pending. When the previous write to the Riak database completes, the local version of the *Bounded Counter*, which absorbed the modifications of all pending operations, is written in the Riak database. If this second conditional write succeeds, all pending operations complete by returning success to the clients. Otherwise, clients are notified of the failure.

D. Transferring Rights

For executing an operation that may violate an invariant, a replica needs to own enough rights. Given that it is impossible to anticipate the rights needed at each replica, it is necessary to redistribute rights among replicas.

In our middleware designs, replicas proactively exchange rights in the background. A replica that has fewer rights than a given threshold periodically asks additional rights from replicas that have more rights (as reflected in the local replica of the *Bounded Counter*). The number of rights requested is half of the difference between the rights of the remote and the local replicas. A replica receiving an asynchronous transfer request never accepts to transfer more than half of the available rights. This strategy provisions replicas with rights without impairing the latency during operation execution.

Nonetheless, it may happen that an operation does not succeed because it has insufficient local rights during execution. In this situation, the programmer can choose to get the rights from a remote replica or abort the operation. Programmatically the decision is made through the *flag* parameter in the *decrement* and *increment* operations, as presented in Figure 1.

To execute a transfer, replica r_i checks the local state to choose the best candidate replica to request rights from (e.g., the remote replica holding more rights), r_j , and sends a transfer request and a flag saying whether it is a synchronous or an asynchronous request. Upon receiving the request, the remote replica r_j checks if it can satisfy the request and if so it executes a local *transfer* operation to move the rights from r_j to r_i . If the request was asynchronous the replication mechanism will asynchronously propagate the update to the requester, otherwise r_j stores the transfer locally and replies to r_i immediately with the new state of the counter.

Replying to every transfer request may lead to a request being satisfied more than once, either because a request message was lost and replayed or because the requester sent the request more than once (possibly to multiple replicas). To avoid this situation, r_i sends in the request to r_j the number of rights transferred from r_j to r_i ($R[j][i]$). The receiver ignores a request if it has already transferred more rights.

A property of the way *transfer* is implemented is that it does not require any strong synchronization between the replica asking for rights and the one providing the rights. Thus, the request for a transfer and synchronization of the information about transferred values can be done completely asynchronously, which simplifies the system design.

E. Fault-tolerance

We now analyze how our middleware designs provide fault-tolerance building on the fault-tolerance of the underlying cloud database. We start by noting that for the *Bounded Counters*, each DC acts as a *Bounded Counter* replica.

A DC is assumed to have sufficient internal redundancy to never lose its state. In Riak, the level of fault-tolerance in each DC can be controlled by changing the size of the quorums used to store data. Thus, an update to an *Bounded Counter* executed in a DC is never lost unless the DC fails forever.

A failure in a node in the DC may cause the DHT used in our server-based middleware to reconfigure. As we explained before, this does not affect correctness as we rely on conditional writes to guarantee that operations of each counter are serialized in each DC.

During a network partition, rights can be used in both sides of the partition – the only restriction is that it is impossible to transfer rights between any two partitioned DCs. If an entire DC becomes unavailable, the rights owned by the unreachable DC become temporarily unavailable. If a DC fails permanently, as the *Bounded Counter* records the rights owned by every replica, it is possible to recover the rights that were owned by the failed DC.

V. EVALUATION

We implemented both middleware designs for extending Riak with numeric invariants and evaluated experimentally the prototypes. This evaluation tries to address the following main questions. (i) How much overhead is introduced by our designs? (ii) What is the performance penalty when the bounds are close to being exceeded? (iii) How does the performance vary with the level of contention for the same counter?

In our designs, operations on *Bounded Counters* are handled by our middleware. All other operations are directly executed in the Riak database. For this reason, our evaluation focus on the performance of *Bounded Counters*, using micro-benchmarks to test different properties of the system.

A. Configurations

In the experiments, we compare the client-based middleware, *BCclt*, and sever-based middleware, *BCsrv*, with the following configurations.

Weakly Consistent Counters (Weak). This configuration uses Riak's native counters operating under weak consistency. Before issuing a decrement, a client reads the current counter value and issue a decrement only if the value is positive.

Strongly Consistent Counters (Strong). This configuration uses Riak's native strong consistency, with the Riak database running in a single DC, which receives requests from clients in the local and remote DCs. As Riak strong consistency cannot be used with Riak data types, the value of the counter is stored as an opaque object for Riak. A counter is updated by reading its value, updating its state if the value is positive, and writing back the new state (using a conditional write).

B. Experimental Setup

Our experiments comprised 3 Amazon EC2 DCs distributed across the globe. The latency between each DC is shown in Table I. In each DC, we use three m1.large machines with 7.5GB of memory for running the database servers and server-based middleware and three m1.large machines for running the clients.

For *Weak*, we used Riak 2.0 Enterprise Edition (EE), with support for geo-replication. For other configurations we used

	RTT (ms)	US-E	US-W	EU
US-East	-	80	96	
US-West	83	-	163	
EU	93	161	-	

TABLE I. RTT LATENCY BETWEEN DATA CENTERS IN AMAZON EC2.

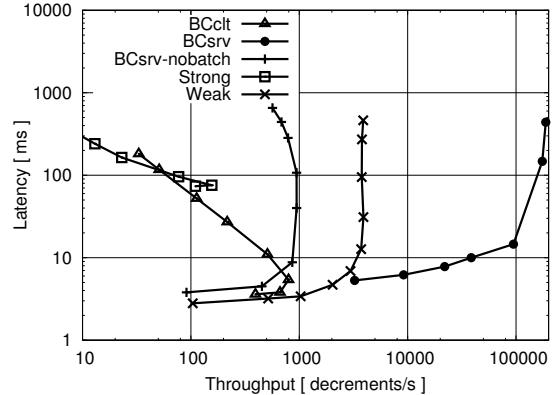


Fig. 6. Throughput vs. latency with a single counter.

Riak 2.0 Community Edition (CE), with support for strong consistency. Both version share the same code, except for the support for strong consistency and geo-replication, which is only available in the enterprise edition.

In *Strong*, data is stored in the US-East DC, which is the location that minimizes the latency for remote clients. In the remaining configurations, data is fully geo-replicated in all DCs, with clients accessing the replicas in the local DC. Riak operations use a quorum of 3 replicas for writes and 1 replica for reads.

C. Single Counter

The objective of this experiment is to evaluate the performance of the middleware designs in contention scenarios. In this case, we use a single counter initialized to a value that is large enough to never break the invariant (10^9). Clients execute 20% of increments and 80% of decrements in a closed loop with a think time of 100 ms. Each experiment runs for two minutes after the initialization of the database. The load is controlled by tuning the number of clients running in each experiment – clients are always evenly distributed among the the client machines.

a) Throughput vs. latency: Figure 6 presents the variation of the throughput vs. latency values as more operations are injected in the system. For the throughput values we consider only the operations that have succeeded, while for the latency we consider the average of all (succeeded or failed) operations. (This only affects the results for *Strong*.)

The results of *BCclt* and *Strong* present a similar trend, which is that the throughput quickly starts degrading with the increase in the load. By analyzing the results of the operations, we found out that this is explained by the fact that the percentage of operations that fail increase very quickly with the number of clients. This is because concurrent updates fail due to the conditional write mechanism – e.g., for *Strong*, 50% of operations fail with 100 clients and 90% with 200 clients. The 3× higher throughput in *BCclt* is explained by the fact that clients execute operations in their local DC, while in *Strong* all operations are sent to a single DC. The higher average latency

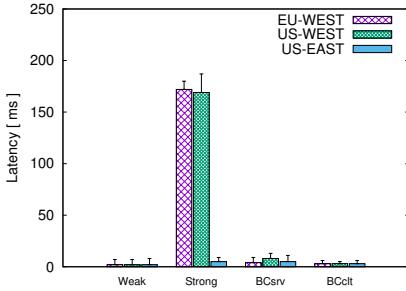


Fig. 7. Median latency with a single counter, per region of clients (the line is the value for the 99th percentile).

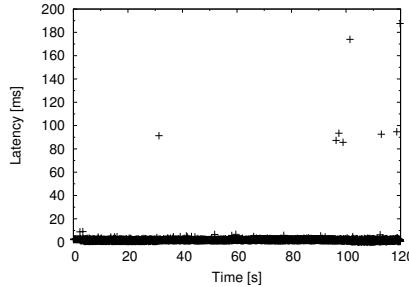


Fig. 8. Latency of each operation over time for BCsrv.

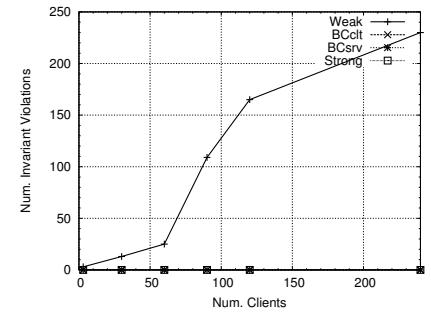


Fig. 9. Decrement executed in excess, violating invariant.

in *Strong* is explained by the latency of operations from remote clients. This explains why we chose to report the latency of all operations, including failed ones: since most of remote operations fail, considering only operations that succeed would lead to latency values close to those of *BCclt*.

The throughput of *Weak* is much larger and it does not degrade with the increase of the load – when it reaches its maximum throughput, increasing the load just leads to an increase in latency. Our server-based middleware, *BCsrv*, has an even higher throughput with slightly higher latency. The higher latency is expected, as the middleware introduces communication overhead. The higher throughput is due to the batching mechanism introduced in *BCsrv*, which batches a sequence of updates into a single Riak write, thus leading to a constant rate of Riak operations. To prove this hypothesis, we have run the same experiment, turning off the batching and writing every update in Riak – results are presented as *BCsrv-nobatch*. In this case, we can observe that the throughput is much lower than *Weak*, but unlike *BCclt*, the throughput does not degrade with the load – the reason for this is that the middleware serializes updates and Riak still sees a constant rate of writes. The same approach for batching multiple operations into a single Riak write could be used with other configurations, such as *Weak*, to improve their scalability.

b) Latency under low load: Figure 7 presents the median latency experienced by clients in different regions when load is low (with 15 threads in each client machine). As expected, the results show that for *Strong*, remote clients experience high latency for operation execution, while local clients are fast. The latency for all the other configurations is very low, with *BCsrv* introducing a slight overhead (of about 2 ms), due to additional communication steps for processing the request. If *Bounded Counters* were added to the Riak database, this overhead could be eliminated.

c) Effects of exhausting rights: In this experiment we evaluate the behavior of our middleware when the value of the counter approaches the limit. To this end, we run the experiment with *BCsrv* and 5 clients executing 100% decrements, initializing the counter with the value 6000 and running an experiment until the rights are all consumed.

Figure 8 shows that most operations take low latency, with a few peaks of high latency whenever a replica needs to obtain additional rights. The number of peaks is small because most of the time the proactive mechanism for exchanging rights is able to provision a replica with enough rights before all rights are used.

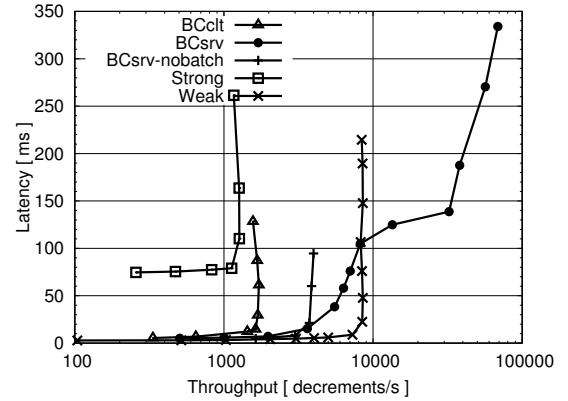


Fig. 10. Throughput vs. latency with multiple counters.

These peaks can occur at any time during the experiment, but are more frequent when the resources are low and replicas exchange rights more often – close to the end of the experiment. After all rights are consumed, the latency remains low because a replica does not ask for rights from replicas that are expected to have no rights (according to the local copy of the *Bounded Counter*). Thus, when all rights are consumed, operations fail locally.

d) Invariant Preservation: To evaluate the severity of the risk of invariant violation, we computed how many decrements in excess were executed with success in the different solutions. The counter is initialized with the value of 6,000 and a variable number of clients execute decrement operations with a think time 100 ms. Figure 9 shows that the invariant was only broken in *Weak*, as expected. The figure shows that an increase in the number of clients directly impacts the severity of the invariant violation. This is because in *Weak* the client reads a counter, checks if its value is greater than the limit and decrements it. Since this is not an atomic operation, the value of the counter can be different between the read and the update, and that difference is directly affected by the number of concurrent updates, which leads to more invariant violations.

D. Multiple Counters

To evaluate how the system behaves in the common case where clients access to multiple counters, we ran the same experiment of Section V-C with 100 counters. For each operation, a client selects the counter to update randomly with uniform distribution. Increasing the number of counters reduces the

contention in each key and contributes to balance the load among nodes.

The results presented in Figure 10 show that both *BCclt* and *Strong* now scale to a larger throughput (when compared with the results with a single key). The reason for this is that by increasing the number of counters, the number of concurrent writes to the same key is lower, leading to a smaller number of failed operations. This in turn increases with the load, as expected. Additionally, when the maximum throughput is reached, the latency degrades but the throughput remains almost constant. The higher average latency in *Strong* is explained by the fact that remote operations have high latency, as shown before.

The *Weak* configuration scales up to a much larger value (9K decrements/s compared with 3K decrements/s for a single counter). As each Riak node includes multiple virtual nodes, when using multiple counters the load is balanced among them - enabling multi-core capabilities to process multiple requests in parallel (whereas with a single node, a single virtual node is used, resulting in requests being processed sequentially).

The results show that *BCsrv* has a low latency close to *Weak*'s as long the number of writes can be handled by Riak's strong consistency mode in a timely manner. In contrast with the experiment with a single counter, Riak's capacity is shared among all the keys, each contributing with writes to Riak. Therefore, as the load increases, writing batches to Riak will take longer to complete and contribute to accumulate latency sooner than in the single key case. Nevertheless, batching still allows multiple client requests to be processed per each Riak operation, leading to a better throughput. The maximum throughput even surpasses the results for the *Weak* configuration. The results for *BCsrv-nobatch*, where each individual update is written using one Riak operation, can be seen as the worst case of our middleware, in which the batching had no effect. Still, since all *BCsrv* operations are local to a given DC and access only a quorum of Riak nodes, one can expect that increasing the local cluster's capacity should have a positive effect both on latency and throughput.

VI. DISCUSSION

In this section we discuss how to extend our approach, to support other could databases and additional invariants.

A. Supporting Other Cloud Databases

Although our middleware designs run on top of the Riak database, it would be immediate to implement a similar prototype running on top of any database that provides conditional writes, such as DynamoDB [11]. Given that we had to implement the geo-replication in the middleware, we do not even require native support for geo-replication.

Alternatively, if the database provides a way to serialize all operations to a given key, it would be easy to adapt the current design. We note that this could be done in two different ways: either the cloud database already supports these strong semantics, in which case there is no need to add any further logic, or the DHT has a way to ensure that messages routed to a given key are delivered in sequence, in which case the DHT can keep track of the latest operation issued to the database.

B. Supporting Other Invariants

Some applications might require that a counter is involved in more than one numeric invariant, and also that some invariants refer to multiple counters – e.g., we may want to have $x \geq 0 \wedge y \geq 0 \wedge x + y \geq K$. To address this, the invariant $x + y \geq K$ can be maintained by a *Bounded Counter* that represents the value of $x + y$. In this case, when updating the value of x (resp. y), it is necessary to update both the *Bounded Counter* for x (resp. y) and for $x + y$, with the operation succeeding if both execute with success. For maintaining such invariants, this needs to be done atomically but not in isolation. In other words, either both *Bounded Counters* are updated or none, however, it is safe for an application to observe a state where only one of the *Bounded Counters* has been updated.

Without considering failures, this allows for a simple implementation where, if one *Bounded Counter* operation fails, the operation in the other *Bounded Counter* is compensated [12] by executing the inverse operation. When considering failures, it is necessary to include some transactional mechanism for guaranteeing that either both updates execute or none – recently, eventually consistent cloud databases started to support such features [19], [20].

A number of other invariants, such as referential integrity and key constraints, can be encoded as numeric invariants, as discussed by Barbará-Milla and García-Molina [5]. Those approaches could be adapted for using *Bounded Counters*.

VII. RELATED WORK

Many cloud databases supporting geo-replication have been developed in recent years. Several of them [11], [19], [20], [2], [15], [7], [26] offer variants of eventual/weak consistency where operations return immediately once executed in a single data center. Such approach is favored for the low latency it can achieve when it selects a data center close the end-user (among several scattered across the world). Each variant addresses particular requirements, such as: reading a causally consistent view of the database [19], [2]; writing a set of updates atomically[20]; or, supporting application-specific or type-specific reconciliation with no lost updates[11], [19], [27], [26], [7]. Our work focuses on the complementary requirement of having counters that enforce a global numeric invariant.

For some applications eventual consistency needs to be complemented or replaced with strong consistency to ensure correctness. Spanner [10] provides strong consistency for the whole database, at the cost of high coordination overhead for all updates. Transaction chains [29] is an alternative that offers transaction serializability with latency proportional to the latency to the first replica accessed.

Often, only specific operations require strong consistency. Walter [27] and RedBlue consistency in Gemini [17] can mix eventual and strong consistency (snapshot isolation in Walter) to allow eventually consistent operations to be fast. PNUTS [9], DynamoDB [26] and Riak [7] also combine weak consistency with per-object strong consistency, by relying on conditional writes that fail if concurrent ones existed. Megastore [4] offers strong consistency inside a partition and weak consistency across partitions. In contrast, our work extends eventual consistency with numeric invariants. This allows, for the specific case of applications that require numeric invariants

to be preserved, their correctness to be met while still allowing most operations to execute in a single replica.

Bailis et al. [3] examine which operations in database systems require coordination for meeting invariants. We provide a low cost solution for operations that may break numeric invariants, which require coordination under their analysis. This is possible because we secure the necessary rights prior to executing the operations, and this way move coordination outside the critical path of operation execution.

Escrow transactions [21], initially proposed for increasing concurrency of transactions in single databases, have also been used for supporting disconnected operation in mobile computing environments either relying on centralized [22], [28] or peer-to-peer [25] protocols for escrow distribution. The demarcation protocol [5] enforces invariants across multiple objects, located in different nodes. The underlying protocols are similar to escrow-based ones, with peer-to-peer interaction. MDCC [14] has recently proposed a variant of this protocol for enforcing data invariants in quorum systems.

Our work combines convergent data-types [24] with ideas from these systems to provide a decentralized approach with replicated data that offers both automatic convergence and invariant-preservation with no central authority. Additionally, we describe, implement and evaluate how such solution can be integrated into existing eventually consistent cloud databases.

Warranties [18] provide time-limited assertions over the state of the database and have been used for improving latency of read operations in cloud databases. The goal of warranties is to support linearizability efficiently, whereas ours is to permit concurrent updates while enforcing invariants.

VIII. CONCLUSION

This paper proposed two middleware designs for extending eventually consistent cloud databases with the ability to enforce numeric invariants. Our designs allow most operations to complete within a single DC by moving the necessary coordination outside of the critical path of operation execution, thus combining the benefits of eventual consistency – low latency, high availability – with those of strong consistency – enforcing global invariants. The evaluation of our prototypes shows that our client-based middleware does not scale when contention is high, but our server-based middleware, featuring a cache and a write batching mechanism, scales even better than the Riak’s native weak consistency mechanism where invariants can be compromised.

ACKNOWLEDGMENTS

This research is supported in part by EU FP7 SyncFree project (609551), FCT/MCT SFRH/BD/87540/2012, PTDC/EEI-SCR/1837/2012 and PEst-OE/EEI/ UI0527/ 2014. The research of Rodrigo Rodrigues is supported by the European Research Council under an ERC Starting Grant.

REFERENCES

- [1] Cassandra counters. <http://wiki.apache.org/cassandra/Counters>.
- [2] ALMEIDA, S., LEITÃO, J. A., AND RODRIGUES, L. Chainreaction: A causal+ consistent datastore based on chain replication. In *Proc. EuroSys ’13* (2013).
- [3] BAILIS, P., FEKETE, A., FRANKLIN, M. J., GHODSI, A., HELLERSTEIN, J. M., AND STOICA, I. Coordination-avoiding database systems. *CoRR abs/1402.2237* (2014).
- [4] BAKER, J., BOND, C., CORBETT, J. C., FURMAN, J. J., KHLORLIN, A., LARSON, J., LEON, J.-M., LI, Y., LLOYD, A., AND YUSHPRAKH, V. Megastore: Providing scalable, highly available storage for interactive services. In *Proc. CIDR 2011* (2011).
- [5] BARBARÁ-MILLÁ, D., AND GARCIA-MOLINA, H. The demarcation protocol: A technique for maintaining constraints in distributed database systems. *The VLDB Journal* 3 (July 1994).
- [6] BASHO Using Data Types. <http://docs.basho.com/riak/2.0.0/dev/using/datatypes/>. Accessed Dec/2014.
- [7] BASHO. Riak. <http://basho.com/riak/>. Accessed Dec/2014.
- [8] BURCKHARDT, S., GOTSMAN, A., YANG, H., AND ZAWIRSKI, M. Replicated data types: Specification, verification, optimality. In *Proc. POPL ’14* (2014).
- [9] COOPER, B. F., RAMAKRISHNAN, R., SRIVASTAVA, U., SILBERSTEIN, A., BOHANNON, P., JACOBSEN, H.-A., PUZ, N., WEAVER, D., AND YERNENI, R. Pnnts: Yahoo!’s hosted data serving platform. *Proc. VLDB Endow. 1* (Aug. 2008).
- [10] CORBETT, J. C., DEAN, J., EPSTEIN, M., FIRES, A., FROST, C., FURMAN, J. J., GHEMAWAT, S., GUBAREV, A., HEISER, C., HOCHSCHILD, P., HSIEH, W., KANTHAK, S., KOGAN, E., LI, H., LLOYD, A., MELNIK, S., MWAURA, D., NAGLE, D., QUINLAN, S., RAO, R., ROLIG, L., SAITO, Y., SZYMANIAK, M., TAYLOR, C., WANG, R., AND WOODFORD, D. Spanner: Google’s globally-distributed database. In *Proc. OSDI’12* (2012).
- [11] DECANDIA, G., HASTORUN, D., JAMPANI, M., KAKULAPATI, G., LAKSHMAN, A., PILCHIN, A., SIVASUBRAMANIAN, S., VOSSHALL, P., AND VOGELS, W. Dynamo: Amazon’s highly available key-value store. In *Proc. SOSP ’07* (2007).
- [12] GARCIA-MOLINA, H., AND SALEM, K. Sagas. In *Proc. SIGMOD’87* (1987).
- [13] KLOPHAU, R. Riak core: Building distributed applications without shared state. In *CUFP ’10* (2010).
- [14] KRASKA, T., PANG, G., FRANKLIN, M. J., MADDEN, S., AND FEKETE, A. Mdcc: Multi-data center consistency. In *Proc. EuroSys’13* (2013).
- [15] LAKSHMAN, A., AND MALIK, P. Cassandra: A decentralized structured storage system. *SIGOPS Oper. Syst. Rev.* 44, 2 (Apr. 2010), 35–40.
- [16] LAMPORT, L. The temporal logic of actions. *ACM Trans. Program. Lang. Syst.* 16, 3 (May 1994), 872–923.
- [17] LI, C., PORTO, D., CLEMENT, A., GEHRKE, J., PREGUIÇA, N., AND RODRIGUES, R. Making geo-replicated systems fast as possible, consistent when necessary. In *Proc. OSDI’12* (2012).
- [18] LIU, J., MAGRINO, T., ARDEN, O., GEORGE, M. D., AND MYERS, A. C. Warranties for faster strong consistency. In *Proc. nsdi’14* (2014).
- [19] LLOYD, W., FREEDMAN, M. J., KAMINSKY, M., AND ANDERSEN, D. G. Don’t settle for eventual: Scalable causal consistency for wide-area storage with cops. In *Proc. SOSP ’11* (2011).
- [20] LLOYD, W., FREEDMAN, M. J., KAMINSKY, M., AND ANDERSEN, D. G. Stronger semantics for low-latency geo-replicated storage. In *Proc. nsdi’13* (2013).
- [21] O’NEIL, P. E. The escrow transactional method. *ACM Trans. Database Syst.* 11, 4 (Dec. 1986), 405–430.
- [22] PREGUIÇA, N., MARTINS, J. L., CUNHA, M., AND DOMINGOS, H. Reservations for conflict avoidance in a mobile database system. In *Proc. MobiSys ’03* (2003).
- [23] SCHURMAN, E., AND BRUTLAG, J. Performance related changes and their user impact. Presented at velocity web performance and operations conference, 2009.
- [24] SHAPIRO, M., PREGUIÇA, N., BAQUERO, C., AND ZAWIRSKI, M. Conflict-free replicated data types. In *Proc. SSS ’11* (2011).
- [25] SHRIRA, L., TIAN, H., AND TERRY, D. Exo-leasing: Escrow synchronization for mobile clients of commodity storage servers. In *Proc. Middleware ’08* (2008).
- [26] SIVASUBRAMANIAN, S. Amazon dynamodb: A seamlessly scalable non-relational database service. In *Proc. SIGMOD ’12* (2012).
- [27] SOVRAN, Y., POWER, R., AGUILERA, M. K., AND LI, J. Transactional storage for geo-replicated systems. In *Proc. SOSP ’11* (2011).

- [28] WALBORN, G. D., AND CHRYSANTHIS, P. K. Supporting semantics-based transaction processing in mobile database applications. In *Proc. SRDS '95* (1995).
- [29] ZHANG, Y., POWER, R., ZHOU, S., SOVRAN, Y., AGUILERA, M. K., AND LI, J. Transaction chains: Achieving serializability with low latency in geo-distributed storage systems. In *Proc. SOSP '13* (2013).